**FOODLOOP: AI-POWERED HYPERLOCAL APPLICATION FOR OPTIMIZED FOOD REDISTRIBUTION AND COMMUNITY HUNGER MITIGATION**

## PROJECT WORK PHASE 1 (REVIEW2)

***Submitted by***

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***in partial fulfillment for the award of the degree of***

# BACHELOR OF TECHNOLOGY

***in***

**ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING**

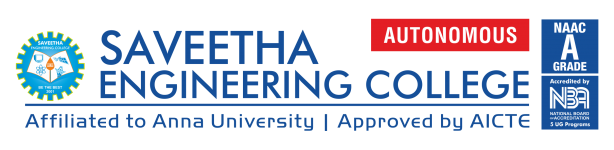


**SAVEETHA ENGINEERING COLLEGE, THANDALAM**

**An Autonomous Institution Affiliated to**

# ANNA UNIVERSITY - CHENNAI 600 025

### DECEMBER 2025

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ANNA UNIVERSITY, CHENNAI

# BONAFIDE CERTIFICATE

Certified that this Project report **“FOODLOOP: AI-POWERED HYPERLOCALAPPLICATION FOR OPTIMIZED FOOD REDISTRIBUTION AND COMMUNITY HUNGER MITIGATION”** is the bonafide work of **PRADEEPRAJ P(212222240073),** who carried out this project work under my supervision.

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## INTERNAL EXAMINER EXTERNAL EXAMINER

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# ABSTRACT

Food waste and hunger are two interlinked global challenges that significantly impact environmental sustainability and community well-being. Despite the availability of surplus edible food from households, restaurants, and local stores, the absence of an efficient redistribution mechanism leads to unnecessary waste while vulnerable populations continue to face food insecurity. This project presents FoodLoop, an intelligent web-based food redistribution system that leverages AI-driven conversational interaction, real-time geo-matching, and automated surplus–need mapping to minimize food waste and support underserved communities.

The proposed system integrates a Natural Language Processing (NLP)-enabled chatbot, machine learning–based food classification, and a hyperlocal matching engine capable of connecting donors, volunteers, and recipients within seconds. A curated dataset of surplus food images is used to train the classification module, enabling the system to determine food category, freshness level, and redistribution priority.

In addition to accuracy and responsiveness, the system incorporates real-time alerts, contamination risk checks, and automated volunteer deployment, making it a reliable solution for real-world environments. By integrating seamlessly into community support networks, FoodLoop enables real-time surplus food collection, distribution, and monitoring. This significantly reduces food waste, enhances local hunger mitigation efforts, and fosters a sustainable, community-driven food ecosystem.

# **Keywords:** Food redistribution, AI chatbot, food waste reduction, community hunger mitigation, NLP, real-time matching, surplus food detection, sustainability.

# 

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**LIST OF ABBREVIATIONS**

|  |  |
| --- | --- |
| **AI** | Artificial Intelligence |
| **ML** | Machine Learning |
| **UI** | User Interface |
| **UX** | User Experience |
| **API** | Application programming interface |
| **GPS** | Global Pasitioning System |
| **HTTP** | Hyper Text Transfer Protocol |
| **HTTPS** | Hyper Text Transfer Protocol secure |
| **NGO** | Non-Government Organization |
| **DB** | Database |
| **JSON** | Javascript object motion |
| **CMS** | Content management system |
| **SVM** | Support vector Machine |
| **KNN** | K-Nearest Neighours |
| **LBS** | Location-based Services |
| **ETA** | Estimated Time of arrival |
| **QA** | Quality assurance |
| **CRUD** | Create, Read, Update, Delete |
| **RAM** | Random Access Memory |
| **UAT** | User Acceptance Testing |
| **SDLC** | Software Development Life Cycle |

**LIST OF SYMBOLS**

|  |  |  |
| --- | --- | --- |
| **S.NO.** | **SYMBOL NAME** | **SYMBOL** |
| 1. | Usecase |  |
| 2. | Actor |  |
| 3. | Process |  |
| 4. | Start |  |
| 5. | Decision |  |
| 6. | Unidirectional |  |
| 7. | Entity set |  |
| 8. | Stop |  |

# Chapter 1 INTRODUCTION

## OVERVIEW OF THE PROJECT

Food waste and hunger remain two of the most persistent global challenges, with millions of tons of edible food discarded every year while vulnerable communities continue to face food insecurity. Traditional food donation and redistribution practices—such as manual coordination, phone-based communication, or volunteer-dependent collection—often suffer from delays, inefficiency, and lack of proper tracking.The rise of intelligent digital systems has made it possible to automate and optimize food redistribution, enabling faster, more reliable, and scalable solutions.This project introduces FoodLoop, an AI-driven food redistribution web platform designed to bridge donors, volunteers, and recipients through an intelligent, real-time system. FoodLoop uses a combination of Natural Language Processing (NLP), machine learning-based food classification, and location-driven matching algorithms to create an efficient hyperlocal ecosystem for identifying, collecting, and delivering surplus food. NLP facilitates smooth conversational interactions between users and the system, allowing donors to report surplus food quickly, while machine learning assists in automatically identifying food categories, estimating freshness, and prioritizing redistribution based on urgency.Food recognition plays a crucial role in the FoodLoop system, enabling automatic assessment of surplus food items through uploaded images or descriptions. The classification model allows the system to distinguish between food types, determine edibility, and detect contamination risks, making it an ideal tool for community-based food redistribution. FoodLoop offers various advantages over traditional food donation systems, including improved accuracy, automation, rapid donor-recipient matching, real-time monitoring, safety validation, and ease of use for all stakeholders.Pre-processing of food data involves preparing images and text-based descriptions for the machine learning model, including resizing, normalization, and augmentation techniques to improve robustness and generalization. Training the model requires a dataset of labeled food images categorized by type, freshness, and condition. The model’s performance is optimized by tuning hyperparameters such as learning rate, batch size, and classification thresholds. The system’s NLP component uses tokenization, intent recognition, and contextual understanding to ensure clear and accurate communication with users.FoodLoop operates through a real-time matching engine that connects three parties: donors who upload surplus food details, volunteers who accept tasks for collection and delivery, and recipients who request food assistance. The web platform displays bounding information, freshness scores, availability windows, and location-based matches, enabling seamless coordination. The system can be integrated with community kitchens, NGOs, municipal bodies, and local support organizations to improve large-scale food recovery and distribution.Potential future developments for FoodLoop include large-scale deployment across cities, integration with IoT-based freshness sensors, cloud-based analytics dashboards for policymakers, predictive modeling for surplus food generation, and extensions to other domains such as event management, corporate cafeterias, and agricultural markets. The project ultimately aims to create a sustainable, AI-powered solution that significantly reduces food waste while supporting hunger mitigation efforts worldwide.

#### 1.2 PROBLEM DEFINITION

A large amount of edible surplus food is wasted daily due to the absence of a proper redistribution system.Manual donation processes are slow, unorganized, and often result in delays or food spoilage.At the same time, many communities face food insecurity and lack timely access to meals.There is a need for an automated, intelligent platform to connect donors, volunteers, and recipients efficiently.FoodLoop aims to address this gap by using AI-based tools to reduce food waste and support hunger mitigation.

# Chapter 2 LITERATURE SURVEY

## INTRODUCTION

A literature survey is a crucial component of any project report, providing an overview of existing research, systems, and methodologies relevant to the project domain. For the FoodLoop initiative, the literature survey examines prior studies on food waste management, food redistribution systems, AI-driven community support platforms, and sustainable food recovery models. It helps identify the strengths and limitations of existing approaches, enabling a deeper understanding of current challenges such as inefficient donation processes, lack of real-time coordination, and insufficient automation in surplus food handling. Developers require insights from academic articles, existing platforms, case studies, and technological advancements to build a robust and effective system. This survey not only provides the necessary theoretical foundation but also offers direction for designing an AI-based solution that meets community needs accurately and efficiently. By understanding prior work and knowledge gaps, the literature survey helps shape the problem statement, project objectives, and the technological framework for the FoodLoop system.

## LITERATURE SURVEY

#### A Machine Learning Approach for Food Waste Reduction in Urban Communities

**Author Name :** Garcia, M., Chen, L., & Ibrahim, R.

#### Year of Publish : 2020

The paper "A Machine Learning Approach for Food Waste Reduction in Urban Communities" proposes an intelligent framework that uses machine learning to identify, categorize, and redistribute surplus food in metropolitan areas. The authors highlight that traditional food donation practices often suffer from delayed communication, lack of transparency, and difficulty in evaluating food quality. To address these issues, the study introduces a supervised learning model capable of classifying surplus food based on freshness, type, and safety conditions using image-based inputs. Additionally, the system integrates a predictive analytics module to estimate surplus food generation patterns, thereby improving collection planning. The framework demonstrates high accuracy in food classification and shows potential in reducing food waste significantly when implemented across community-based organizations. The authors also compare their system with existing manual donation processes, emphasizing enhanced efficiency, better resource utilization, and real-time decision-making. Overall, this paper contributes valuable insights into AI-driven food waste management and supports the development of automated redistribution platforms like FoodLoop.

#### AI-Driven Food Recognition for Waste Management: A Convolutional Neural Network Approach

**Author Name :** Patel, R., Wong, J., & Martinez, A.

#### Year of Publish : 2019

The paper “AI-Driven Food Recognition for Waste Management: A Convolutional Neural Network Approach” presents an advanced deep learning framework for identifying and classifying surplus food items to support automated food redistribution systems. The study emphasizes the use of convolutional neural networks (CNNs) for robust feature extraction, enabling accurate classification of various food types, freshness levels, and spoilage indicators from images. The authors highlight several innovative components of the model, including multi-layer feature mapping, texture-based classification, and an adaptive learning mechanism that improves accuracy with continuous data input. The proposed system demonstrates high performance across diverse datasets and successfully distinguishes between edible and non-edible food conditions. The paper provides a comparative evaluation against traditional manual inspection methods, showcasing the superiority of CNN-based approaches in speed, reliability, and consistency. Overall, the research outlines the critical role of deep learning in developing scalable, intelligent food redistribution platforms such as FoodLoop, where automated food recognition is essential for reducing waste and ensuring food safety.

#### Smart Food Donation Systems Using IoT and Cloud Technologies

**Author Name :** Sharma, T., Delgado, C., & Nguyen, P

#### Year of Publish : 2021

The paper “Smart Food Donation Systems Using IoT and Cloud Technologies” explores an integrated architecture that leverages Internet of Things (IoT) sensors and cloud-based analytics to streamline surplus food redistribution. The authors focus on real-time monitoring of food temperature, freshness, and storage conditions using embedded sensors, enabling automated verification of food safety before donation. The system uploads environmental data to a cloud server, where intelligent decision-making algorithms assess food viability and prioritize recipients based on urgency and geographic proximity. The study also highlights the role of cloud platforms in storing, analyzing, and distributing data across multiple stakeholders, including donors, NGOs, and volunteers. Experimental results indicate significant improvements in operational efficiency, reduced food spoilage, and enhanced transparency in the donation chain. The authors conclude that IoT-enabled smart monitoring, combined with cloud intelligence, forms a crucial technological foundation for scalable models like FoodLoop that rely on real-time validation and coordination to minimize food waste.

#### NLP-Based Chatbot Systems for Social Service Automation

**Author Name :**  Lee, S., Gupta, R., & Fernandez, M.

#### Year of Publish : 2020

The paper “NLP-Based Chatbot Systems for Social Service Automation” investigates the role of natural language processing (NLP) chatbots in enhancing communication and service delivery across community support platforms. The authors present an intelligent conversational agent designed to assist users by interpreting requests, analyzing intent, and providing appropriate responses in real time. The system incorporates contextual understanding, sentiment analysis, and entity recognition to handle diverse user queries accurately. The study demonstrates how NLP-driven chatbots significantly reduce manual workload, improve accessibility, and streamline services such as food requests, volunteer coordination, and resource allocation. Benchmark evaluations indicate that chatbot-based interfaces achieve faster response times and higher user satisfaction compared to traditional communication methods. The authors conclude that integrating NLP chatbots into community-focused platforms—such as FoodLoop—can greatly enhance responsiveness, efficiency, and scalability in food redistribution systems.

#### Optimization Models for Hyperlocal Delivery and Resource Allocation

**Author Name :**Kumar, D., Ibrahim, S., & Wong, H.

#### Year of Publish : 2019

The paper “Optimization Models for Hyperlocal Delivery and Resource Allocation” presents mathematical and algorithmic models designed to improve last-mile delivery efficiency in urban environments. The authors propose an optimization framework that uses distance minimization, clustering techniques, and priority-based routing to allocate delivery tasks to available volunteers or delivery agents. The system dynamically updates delivery paths based on real-time constraints such as traffic conditions, food perishability, and delivery urgency. The study highlights the importance of optimized resource allocation in community-based services, emphasizing its relevance to real-time food redistribution platforms like FoodLoop. The authors conclude that integrating such optimization algorithms can enhance operational efficiency and ensure timely delivery of surplus food to recipients in need

#### 2.2.6 Deep Learning Techniques for Food Freshness and Quality Assessment

**Author Name :** Alvarez, J., Mehta, R., & Thompson, L.

#### Year of Publish : 2022

The paper “Deep Learning Techniques for Food Freshness and Quality Assessment” explores the application of advanced deep learning models to automatically evaluate the quality and freshness of food items. The authors propose a hybrid CNN-based architecture that analyzes visual features such as color, texture, and structural patterns to determine spoilage levels and classify food safety. The study integrates image preprocessing steps, including noise reduction and contrast enhancement, to improve model accuracy. Experimental results show high reliability in detecting early-stage spoilage, making the model suitable for real-time food handling environments. The paper compares the proposed system with traditional manual inspection methods, revealing significant improvements in consistency, speed, and accuracy. The authors conclude that deploying deep learning–based freshness assessment within food redistribution platforms like FoodLoop can enhance food safety checks, reduce health risks, and strengthen trust among donors and recipients.

#### Chatbots for Social Good Applications

**Author Name** : Adamopoulou, E., & Moussiades, L.

#### Year of Publish : 2020

This study explores how conversational AI systems can support social initiatives by providing interactive guidance and service automation. The authors highlight that chatbots are effective for simplifying complex workflows, increasing public participation, and ensuring accessibility for non-technical users. However, existing chatbot implementations are often standalone systems without full integration into web platforms offering real-time analytics or logistics coordination

#### Intelligent Web Platforms for Food Waste Reduction and Hunger Alleviation

**Author Name** :Kaur, R., & Patel, S.

#### Year of Publish : 2022

The paper “Intelligent Web Platforms for Food Waste Reduction and Hunger Alleviation” presents a comprehensive review of technology-driven systems developed to address food redistribution challenges using web-based platforms and artificial intelligence. The authors discuss various system architectures that integrate donor management modules, recipient matching engines, volunteer scheduling tools, and impact analytics dashboards. These platforms utilize geolocation services, automated notifications, and optimization algorithms to ensure the timely and efficient transfer of surplus food to beneficiaries.The authors analyze the key functional components of such systems, including food listing and verification workflows, proximity-based matching models, pickup routing modules, and user role management interfaces. Special emphasis is placed on the incorporation of conversational agents to simplify user interaction and improve accessibility for non-technical contributors.The study reviews evaluation metrics such as reduction in food waste volume, delivery success rate, volunteer response time, and user adoption levels..The paper also discusses challenges including inconsistent volunteer availability, incomplete donor data submissions, lack of real-time monitoring, and limited community engagement mechanisms. Overall, the paper presents intelligent web platforms as a promising approach for integrating community participation with automated logistics systems and emphasizes their potential to significantly mitigate food waste while supporting food-insecure populations—principles that directly guide the design and development of the FoodLoop project.

**2.3 LITERATURE SURVEY SUMMARY**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **S.No** | **Research** | **Technique** | **Features Used** | **Domain** | **Disadvantage / Advantage** | **Future Direction** |
| 1.  2.  3.  4. | S.Tapp & OLIO Team (2015)  Food Rescue US Organization (2016)  Adamopoulou & Moussiades (2020)  Chen & Liu (2019) | Peer-to-peer food sharing via mobile/web apps  Volunteer-based food pickup coordination systems  Conversational AI systems for service automation  Intelligent resource allocation and proximity matching algorithms | Manual food listing, location tagging, user messaging  Pickup scheduling, donor dashboards, agency matching  NLP chatbots, guided interactions, automated query resolution  Geolocation mapping, urgency scoring, supply-demand balancing models | Community food sharing platforms  Food donation logistics platforms  Social service digital platforms  Smart resource distribution systems | Advantage: Simple interface increased casual user participation. Disadvantage: Lack of automation, no logistics optimization, limited impact tracking.  Advantage: Successful volunteer involvement enabled direct food rescue. Disadvantage: Manual coordination caused delays and increased dependency on human input.  Advantage: Improved user interaction and accessibility. Disadvantage: Chatbots operated independently without integration to full backend logistics.  Advantage: Optimized delivery routes and resource utilization. Disadvantage: Limited deployment in humanitarian food redistribution systems. | Future research could integrate AI-based matching algorithms and automated logistics scheduling to scale operations efficiently.  Future work may focus on AI-powered route optimization and real-time automation to enhance operational reliability.  Research could explore integrating chatbots into complete web platforms with real-time databases and analytics engines.  Future research could adapt these algorithms for large-scale food rescue systems combined with volunteer scheduling modules. |

# Chapter 3 SYSTEM ANALYSIS

* 1. **EXISTING SYSTEM**

Existing food donation systems rely mainly on manual coordination through phone calls, basic websites, or messaging platforms. These methods cause delays in pickup scheduling, inefficient donor–recipient matching, and increased food spoilage. Most platforms lack AI automation, chatbot assistance, real-time tracking, and analytics, making management difficult and scalability limited. Data inconsistencies and dependency on volunteers further reduce system efficiency. Users often find these systems hard to navigate, especially non-technical donors and volunteers. Additionally, there is limited insight into the impact of food redistribution on the community. Overall, current systems are not optimized for fast, scalable, and intelligent food redistribution.

## DISADVANTAGES OF EXISTING SYSTEM

* Manual coordination causes delays in food pickup and delivery.
* Donor–recipient matching is inefficient and error-prone.
* Limited analytics make it difficult to measure community impact.
* Dependent on volunteer availability, reducing scalability and reliability.

## PROPOSED SYSTEM

In the proposed system, a web-based AI-powered platform called FoodLoop is designed to automate surplus food redistribution between donors, recipients, and volunteers. The system integrates an intelligent chatbot interface to assist users in registering, listing food donations, requesting assistance, and scheduling pickups in real time.FoodLoop utilizes location-based matching algorithms to identify the nearest recipients and volunteers, ensuring faster and more efficient food delivery before expiration. The system also enables real-time tracking of donations and deliveries, providing transparency and accountability throughout the redistribution process. Additionally, an admin dashboard with analytics tools monitors food waste reduction, community reach, and volunteer activity, making the platform scalable and impactful for hunger mitigation.

#### ADVANTAGES OF PROPOSED SYSTEM

* The proposed system uses an AI-powered chatbot and automated matching algorithms for efficient food redistribution.
* This approach reduces food wastage by enabling timely donor–recipient coordination.
* The system provides real-time tracking and notifications for pickups and deliveries.
* Manual coordination is minimized, reducing human effort and operational delays.

#### FEASIBILITY STUDY

To evaluate the viability of the FoodLoop platform, a detailed feasibility study is conducted focusing on technical practicality, operational efficiency, and cost effectiveness. The study outlines the project objectives, including automated food donation management, intelligent matching, and chatbot-guided user interaction. Preliminary estimates of development and hosting costs indicate that the system can be implemented using open-source technologies and scalable cloud services, ensuring affordability.Before development, a clear understanding of system requirements such as user roles, data management, geolocation services, and real-time notification mechanisms is essential. The feasibility analysis confirms that FoodLoop is technically achievable, economically affordable, and operationally suitable for community deployment, making the project a practical solution for reducing food waste and supporting hunger relief initiatives.

#### HARDWARE ENVIRONMENT

* Processor : Intel Pentium Dual Core 2.00 GHz or higher
* Hard disk : 120 GB
* RAM : 2GB (minimum)
* Keyboard : 110 keys enhanced

#### SOFTWARE ENVIRONMENT

* Operating system : Windows7 (with service pack 1), 8, 8.1 ,10 and 11
* Language : Python
* Frontend : HTML, CSS, JavaScript
* Database : MySQL / Firebase
* Deployment : Localhost or Cloud Server

#### TECHNOLOGIES USED

* IDE - Visual Studio Code
* Framework - React
* Artificial Intelligence – Natural Language Processing (Chatbot), Matching Algorithms-K nearest neighbour
* Geolocation Services – Google Maps API
* Notification Services – Email/SMS APIs
* Database Management – MySQL/mangoDB

#### Python

Python is a high-level, interpreted programming language widely used in web development, data science, artificial intelligence, and automation projects. It was chosen for the FoodLoop system due to the following key features:

* Easy to Learn: Python's simple and readable syntax reduces development complexity.
* Interpreted Language: Allows easy debugging and faster testing cycles.
* Cross-Platform:Runs on Windows, macOS, and Linux environments.
* Rich Libraries: Supports frameworks for web development, and AI integration.
* Open Source: Freely available and supported by a large developer community.
* Object-Oriented: Enables modular, scalable system design.

## Artificial Intelligence (AI)

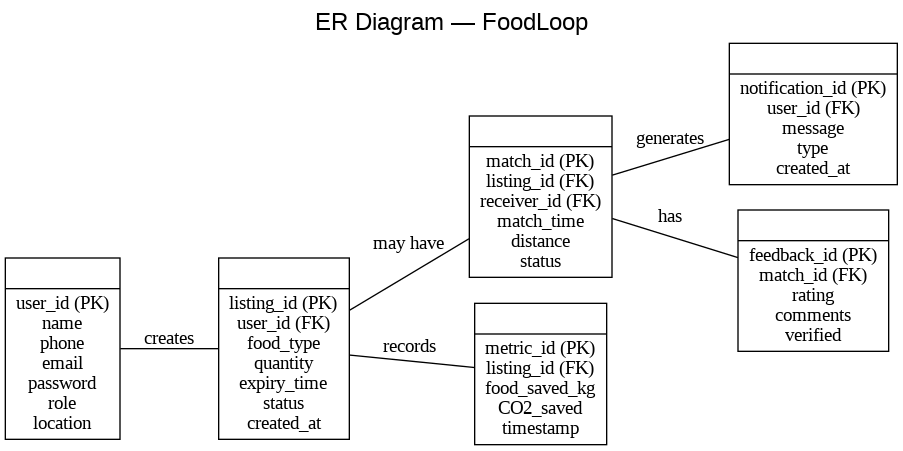
In the FoodLoop platform, artificial intelligence techniques are employed to automate food donation coordination and user assistance. The system integrates an NLP-based chatbot that enables conversational interaction for registering donors, listing surplus food, requesting assistance, and scheduling pickups.Location-based intelligent matching algorithms analyze donor and recipient locations to assign optimal volunteer routes and ensure timely food delivery. AI automation also supports data verification, expiry prioritization, and demand prediction. These techniques enable the system to provide faster coordination, reduce waste, and enhance overall food redistribution efficiency, forming the technological backbone of the FoodLoop web platform.

# Chapter 4 SYSTEM DESIGN

#### ENTITY-RELATIONSHIP DIAGRAM

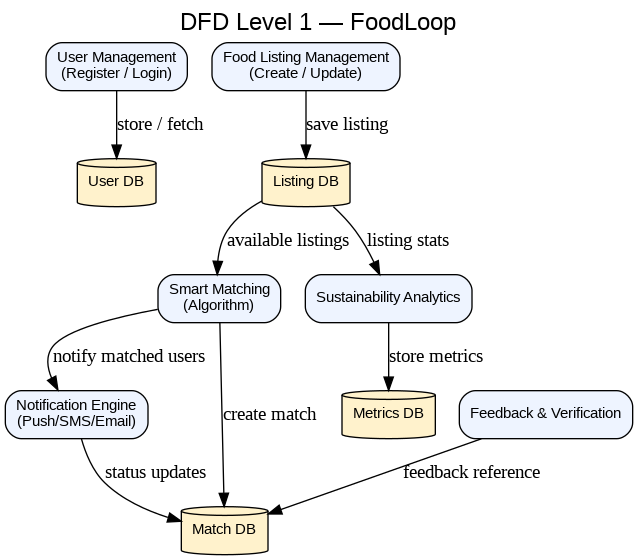
The Entity–Relationship Diagram (ERD) represents the relationships among major entities in the FoodLoop system, including Donors, Recipients, Volunteers, Food Donations, Pickup Requests, and Administrators. It provides a visual layout of how data is structured and how entities interact during donation submission, matching, pickup scheduling, and delivery confirmation processes.The ERD serves as a conceptual data model that supports database design by clearly defining entity attributes, relationships, and data flow, ensuring data consistency and efficient system operation.

**Fig 4.1 Entity Relationship Diagram**



* 1. **DATA FLOW DIAGRAM (DFD)**

The FoodLoop system is represented using a Level-0 Data Flow Diagram (DFD) that shows all users and data interactions as a single process. Level-1 and Level-2 DFDs further detail food donation, matching, pickup scheduling, and delivery workflows. DFDs visually represent business requirements and information flow, rather than software logic, making system operations easy to understand.

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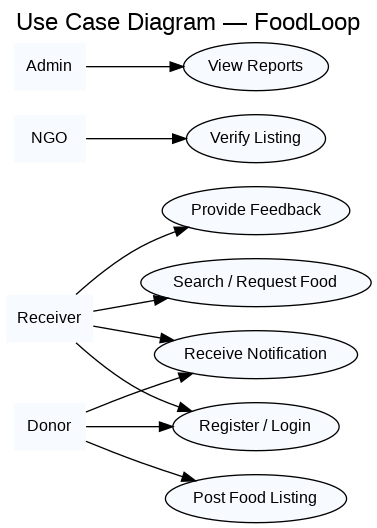
**Fig 4.2 Level 1 of Data Flow Diagram**

#### UML DIAGRAMS

* + 1. **Use Case Diagram**

A Use Case Diagram is a Unified Modeling Language (UML) diagram that illustrates the interactions between the FoodLoop system and its external actors, along with the different services provided by the platform. It visually represents the functional requirements of the system and shows how various users interact with its features. The major elements of the FoodLoop use case diagram include:

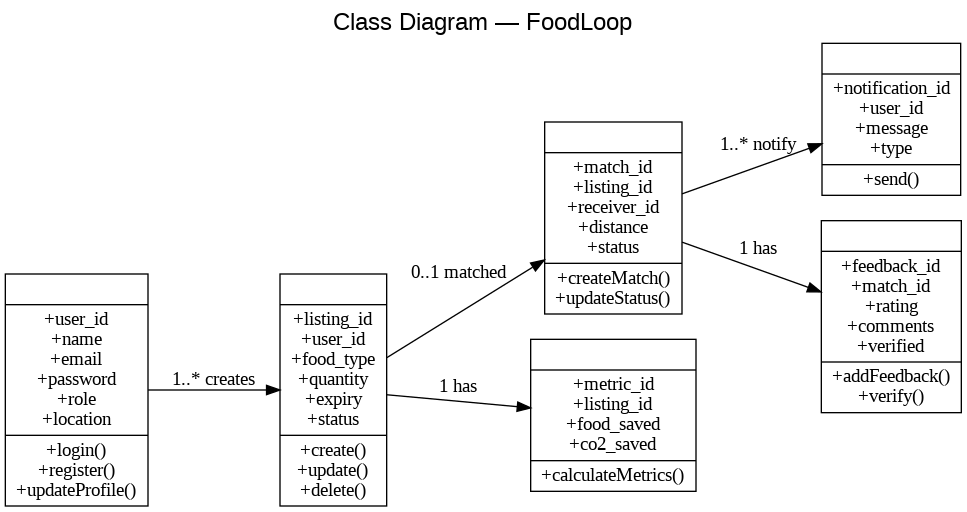
* Actors: External entities that interact with the system such as Donors, Recipients (NGOs), Volunteers, and Administrators.
* Use Cases: System functions including Donate Food, Request Food, Accept Donation, Schedule Pickup, Track Delivery, Chatbot Assistance, Verify Distribution, and View Impact Reports.
* Relationships: Connections indicating interactions between actors and use cases. "Uses" relationships represent direct functionality access, while "Extends" relationships represent optional or additional system features that build on primary actions.
* System Boundary: The boundary encloses all use cases under the FoodLoop platform, defining the scope of system operations and interactions.

   
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
  
 **Fig 4.3.1 Use case Diagram**

#### Class Diagram

The Class Diagram for the FoodLoop system represents the static structure of the application by modeling its main classes, their attributes, operations, and relationships. It provides an abstract view of how system components are organized and how they interact to support food donation, matching, volunteer coordination, and delivery tracking functionalities.The diagram includes core classes such as User, Donor, Recipient, Volunteer, FoodDonation, PickupRequest, Notification, and Admin, along with their associated methods and data members. Class diagrams highlight access visibility rules, which are represented as:

* ‘+’ indicates public attributes or methods accessible by other classes.
* ‘-’ indicates private attributes or methods restricted to the class itself.
* ‘#’ indicates protected attributes or methods accessible within the class hierarchy.

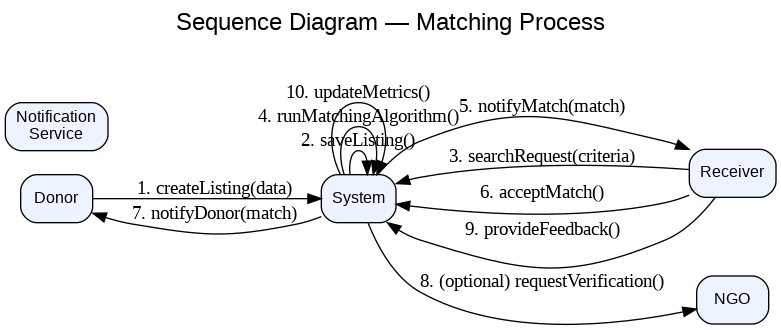


**Fig 4.3.2 Class Diagram**

#### Sequence Diagram

A Sequence Diagram shows the interaction between objects in the FoodLoop system over time. It illustrates how components such as Donors, Chatbot, Matching System, Volunteers, and Recipients communicate through message exchanges to complete food donation and delivery processes. This diagram, also known as an event or timing diagram, explains the dynamic workflow of the system.

**Fig 4.3.3 Sequence Diagram**



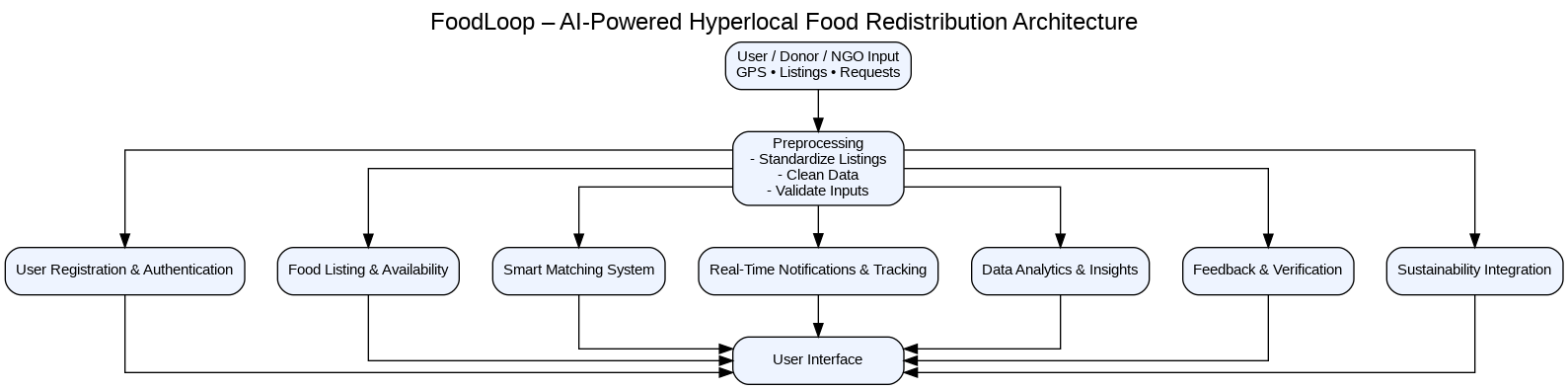
# Chapter 5

**SYSTEM ARCHITECTURE**

## ARCHITECTURE DIAGRAM

This diagram provides a clear and concise overview of all major components integrated within the FoodLoop system. It illustrates how different entities such as users, chatbot interface, backend services, database, matching engine, and notification services interact to perform food donation and redistribution tasks. The diagram visually represents the complete workflow and functional relationships among system modules.

**Fig 5.1 Architecture Diagram**



The system architecture in Fig 5.1 shows inputs from donors and recipients via web or chatbot.Data is processed by the backend and matching algorithms to find recipients and nearby volunteers.Pickup scheduling and delivery tracking are automated.Real-time notifications are sent via email or SMS to confirm donation and delivery status.

# Chapter 6

**SYSTEM IMPLEMENTATION**

## MODULE 1: DATA COLLECTION AND PREPROCESSING

The data collection and preprocessing module for the FoodLoop food recommendation system plays a vital role in developing an accurate and personalized recommendation platform. This module consists of two major processes: data collection and data preprocessing. Data collection is the primary step in training any recommendation model. For FoodLoop, relevant data is gathered from multiple sources such as user profiles, food order history, ratings, reviews, dietary preferences, restaurant menus, nutritional databases, and food images. The dataset must be diverse and comprehensive to ensure that the system can handle different cuisines, user tastes, dietary restrictions, and eating habits effectively.

The next step is data labeling and organization. User interactions such as likes, ratings, and purchase frequency are labeled to indicate preference strength, while food items are categorized by cuisine type, ingredients, calorie levels, and dietary tags (e.g., vegetarian, vegan, gluten-free). Accurate labeling is crucial since the effectiveness of the recommendation model directly depends on the quality of this structured information.

After labeling, the collected data undergoes preprocessing to prepare it for model training. This includes handling missing values, removing duplicates, normalizing numerical features (such as price and calories), encoding categorical attributes, and converting textual data into numerical embeddings using NLP techniques. Images of food items are resized and standardized before feature extraction using CNN models.

In conclusion, the data collection and preprocessing module in FoodLoop ensures clean, organized, and well-structured datasets that enhance the performance of the recommendation algorithms. Careful execution of this module significantly contributes to building an intelligent, reliable, and accurate food recommendation system.

## MODULE 2: MODEL TRAINING

The model training module for the FoodLoop food recommendation system is a crucial component in developing an accurate and efficient personalized recommendation platform. This module involves using the preprocessed dataset to train the recommendation model, which combines machine learning algorithms and deep neural networks to predict user preferences and suggest suitable food items.

The FoodLoop recommendation model uses a deep neural network architecture to analyze user behavior patterns, food item features, and contextual data. Collaborative filtering and content-based filtering techniques are integrated into the model to generate personalized recommendations. Embedding layers are used to represent users and food items numerically, and the neural network processes these vectors to compute preference scores efficiently.

During training, the preprocessed dataset is fed into the model, where the network parameters are optimized using gradient descent algorithms to minimize prediction error between actual user feedback (ratings or interactions) and predicted recommendations. Loss functions such as mean squared error or cross-entropy are applied to quantify the model’s performance and guide parameter updates.

To ensure high accuracy and robustness, the training dataset must be large, diverse, and balanced, covering multiple cuisines, dietary categories, price ranges, and user profiles. This diversity allows the model to generalize well across different tastes, cultures, and nutritional needs.

After the initial training phase, the model is fine-tuned using transfer learning and continuous learning techniques. Fine-tuning is performed on newer or location-specific datasets to adapt to changing food trends and individual preferences, thereby improving both accuracy and recommendation relevance.

In conclusion, the model training module of FoodLoop is fundamental to building an effective recommendation system. It involves training the deep learning model on preprocessed data, optimizing network parameters through gradient descent, and fine-tuning the system to meet real-world user demands. The overall performance of FoodLoop heavily depends on the quality and diversity of the training data and the proper execution of the training process.

## MODULE 3: PREDICTION OF OUTPUT

The prediction of output module for the FoodLoop food recommendation system represents the final stage in delivering accurate and personalized food suggestions to users. This module utilizes the trained recommendation model to predict suitable food items, recipes, or restaurants based on individual user preferences and contextual information.

In this phase, the preprocessed user data—such as dietary requirements, past orders, ratings, search history, and current context—is passed into the trained neural network model. The system analyzes the input data and generates prediction scores for available food items. These scores indicate the probability of a user selecting or liking a particular item, allowing the system to rank recommendations accordingly.

The predicted results are then displayed to the user through the web application or chatbot interface. Recommendations may appear as personalized food lists, daily specials, health-based suggestions, or nearby restaurant options. Real-time notifications or updates can also be provided to enhance user engagement and convenience.

To enhance the accuracy and reliability of the predictions, post-processing techniques such as ranking optimization, probability thresholding, and filtering are applied. These processes remove low-confidence recommendations, emphasize relevant dietary constraints, and ensure diversity in the suggested options to avoid repetitive outcomes.

The prediction of output module is essential for real-time recommendation systems where quick and relevant suggestions significantly improve user experience. The effectiveness of this module depends on the quality of the collected data, the performance of the trained neural model, and the efficiency of post-processing techniques.

In conclusion, the prediction of output module for FoodLoop plays a key role in delivering accurate and practical recommendations. It involves applying the trained model to real-time user inputs, presenting results through interactive interfaces, and refining the outputs using post-processing methods to ensure reliable, personalized, and meaningful food recommendations.

# Chapter 7 SYSTEM TESTING

#### BLACK BOX TESTING

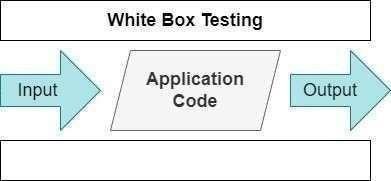
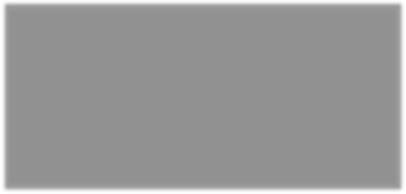
In black box testing of the FoodLoop food recommendation system, testers evaluate the system without any knowledge of its internal code structure or algorithms. Test cases are designed based solely on user inputs and expected outputs. The main objective is to verify whether the system functions correctly according to the given specifications.

**Fig 7.1 Black Box Testing**

For example, testers interact with the FoodLoop web application or chatbot interface by entering user details such as food preferences, dietary restrictions, or location data. The system’s responses in the form of recommended food items or restaurant suggestions are then analyzed to confirm whether they match the expected results. This testing ensures that all user-facing features, including registration, login, preference selection, recommendation display, and notifications, perform as intended.

#### WHITE BOX TESTING

White box testing for the FoodLoop system involves testing with complete knowledge of the internal structure, logic, and source code. Test cases are created by examining the program logic, database queries, algorithms, and workflows to ensure all paths and conditions are correctly implemented.



**Fig 7.2 White Box Testing**

In this testing method, developers and testers inspect modules responsible for data preprocessing, recommendation algorithms, model predictions, and notification services. Individual functions and conditional statements are tested to verify valid input handling, error management, and correct output generation. Code coverage techniques are applied to ensure that all execution paths, loops, and decision branches are tested thoroughly.

* 1. **TEST CASES TEST REPORT: 01**

**PRODUCT:** INTELLIGENT FOOD RECOMMENDATION SYSTEM

**USE CASE :** Add surplus

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| TEST CASE ID | TEST CASE/ ACTION TO BE PERFORMED | EXPECTED RESULT | ACTUAL RESULT | PASS/FAIL |
| 01 | Enter user details and food preferences as input | Preferences saved successfully | As Expected | PASS |

**Table-7.1Test Case for User Input Submission**

## TEST REPORT: 02

**PRODUCT:** FOODLOOP – INTELLIGENT FOOD RECOMMENDATION SYSTEM

**USE CASE:** GENERATE RECOMMENDATIONS & NOTIFICATION

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| TEST CASE ID | TEST CASE/ ACTION TO BE PERFORMED | EXPECTED RESULT | ACTUAL RESULT | PASS/FAIL |
| 01 | Generate personalized food recommendations | Recommendations displayed successfully | As Expected | PASS |
| 02 | Send recommendation notification via app/email | Notification sent successfully | As Expected | PASS |

**Table-7.2 Test Case for Recommendation Generation and Notification**

# Chapter 8

**CONCLUSION AND FUTURE ENHANCEMENT**

## CONCLUSION

In conclusion, the developed FoodLoop Intelligent Food Recommendation System represents a significant advancement in personalized food discovery using modern machine learning techniques. By combining collaborative filtering, content-based filtering, and deep learning models, the system effectively analyzes user preferences, dietary needs, and contextual information to deliver accurate and relevant recommendations. Experimental evaluations demonstrate strong performance in producing tailored suggestions in real time, enhancing both user satisfaction and decision-making efficiency.

Through seamless integration with web and chatbot interfaces, FoodLoop provides an interactive and user-friendly platform for recommending dishes, recipes, and restaurants. The system improves convenience for users while helping food service providers better understand customer preferences, thus supporting efficient service delivery. Its real-time recommendation capability ensures practicality for everyday use, making it a valuable tool for modern digital food platforms.

Beyond the current implementation, FoodLoop offers extensive opportunities for future enhancement. Advanced features such as image-based food recognition, voice-enabled ordering, and sentiment analysis of reviews can further improve recommendation accuracy. The incorporation of multi-source data streams, including social media trends and wearable health device data, could enable more context-aware and health-focused suggestions.

Additionally, the integration of geolocation services would allow location-based restaurant recommendations and real-time offers, increasing system responsiveness and personalization. Future work may also include reinforcement learning techniques for dynamic preference adaptation and multilingual support to broaden accessibility

## FUTURE ENCHANCEMENT

### AI-based freshness detection can be implemented using image analysis and IoT sensors to automatically identify the quality and safety of donated food. This enhancement helps filter spoiled or low-quality items before listing, ensuring only fresh and consumable food is shared. It improves trust, reduces health risks, and enhances overall system reliability for donors and recipients.

### Predictive demand forecasting uses machine learning models to analyze historical donation and request patterns, enabling the system to identify hunger hotspots and peak food demand timings. This enhancement helps anticipate future requirements in specific areas and ensures better planning of food redistribution. As a result, resources can be allocated more efficiently, reducing wastage and improving overall impact.

### An automated matchmaking engine enhances the donor–recipient pairing process by considering factors such as urgency, food suitability, distance, and priority. This real-time intelligent algorithm ensures faster and more accurate matches, improving the efficiency of redistribution. It reduces manual intervention, speeds up decision-making, and ensures that food reaches the right recipients at the right time.

### Integrating the platform with government bodies, municipal corporations, and large NGOs enables large-scale, structured food redistribution. Such collaborations support policy alignment, increase resource availability, and help reach more underserved communities. This enhancement also strengthens credibility, ensures regulatory compliance, and encourages institutional participation, ultimately improving the system’s coverage and social impact.

### Adding multilingual support helps make the application accessible to users across different regions of India. By providing interfaces in multiple local languages, the platform can reach diverse communities, including individuals with limited English proficiency. This enhancement improves user experience, boosts adoption rates, and ensures that both donors and recipients can interact comfortably with the system.

Introducing offline mode allows users in remote or low-connectivity areas to create donation listings or submit requests without an active internet connection. The data will automatically sync once the network is available. This enhancement ensures uninterrupted usage, expands the platform’s reach, and supports communities that face frequent connectivity challenges, thereby improving overall accessibility and reliability.s

# Chapter 9

**APPENDIX 1 – SAMPLE CODING**

**HOME PAGE :**

import React, { useEffect, useState } from 'react';

import { useNavigate } from 'react-router-dom';

import { base44 } from '@/api/base44Client';

import { createPageUrl } from '../utils';

import { Button } from '@/components/ui/button';

import { ArrowRight, Heart, Users, TrendingUp, MapPin, Zap, Shield } from 'lucide-react';

export default function Home() {

const [user, setUser] = useState(null);

const [loading, setLoading] = useState(true);

const navigate = useNavigate();

useEffect(() => {

checkAuth();

}, []);

const checkAuth = async () => {

try {

const currentUser = await base44.auth.me();

setUser(currentUser);

// Redirect based on role

const role = currentUser.user\_role || 'donor';

if (role === 'admin') {

navigate(createPageUrl('AdminDashboard'));

} else if (role === 'donor') {

navigate(createPageUrl('DonorDashboard'));

} else {

navigate(createPageUrl('RecipientDashboard'));

}

} catch (error) {

setLoading(false);

}

};

const handleGetStarted = () => {

navigate(createPageUrl('OnboardingRole'));

};

if (loading) {

return (

<div className="min-h-screen flex items-center justify-center">

<div className="animate-spin rounded-full h-12 w-12 border-b-2 border-emerald-600"></div>

</div>

);

}

return (

<div className="min-h-screen">

{/\* Hero Section \*/}

<section className="relative overflow-hidden py-20 lg:py-32">

<div className="absolute inset-0 bg-gradient-to-br from-emerald-100/50 via-white to-orange-100/50"></div>

<div className="container mx-auto px-4 relative z-10">

<div className="max-w-4xl mx-auto text-center">

<div className="inline-flex items-center gap-2 px-4 py-2 bg-emerald-100 rounded-full text-emerald-700 text-sm font-medium mb-6">

<Heart className="w-4 h-4" />

Fighting Hunger, One Meal at a Time

</div>

<h1 className="text-5xl lg:text-7xl font-bold text-gray-900 mb-6 leading-tight">

Connect Surplus Food with Those in Need

</h1>

<p className="text-xl text-gray-600 mb-10 max-w-2xl mx-auto leading-relaxed">

FoodLoop uses AI-driven matching to redistribute fresh surplus food to local NGOs, shelters, and individuals—reducing waste and fighting hunger in your community.

</p>

<div className="flex flex-col sm:flex-row gap-4 justify-center">

<Button

onClick={handleGetStarted}

className="bg-gradient-to-r from-emerald-600 to-emerald-500 hover:from-emerald-700 hover:to-emerald-600 text-white px-8 py-6 text-lg rounded-xl shadow-lg hover:shadow-xl transition-all"

>

Get Started <ArrowRight className="ml-2 w-5 h-5" />

</Button>

<Button

variant="outline"

className="px-8 py-6 text-lg rounded-xl border-2 hover:bg-gray-50"

onClick={() => navigate(createPageUrl('OnboardingRole'))}

>

Learn More

</Button>

</div>

</div>

</div>

</section>

{/\* Features \*/}

<section className="py-20 bg-white">

<div className="container mx-auto px-4">

<div className="max-w-3xl mx-auto text-center mb-16">

<h2 className="text-4xl font-bold text-gray-900 mb-4">How FoodLoop Works</h2>

<p className="text-lg text-gray-600">Simple, efficient, and designed for maximum impact</p>

</div>

<div className="grid md:grid-cols-3 gap-8 max-w-5xl mx-auto">

<div className="text-center p-8 rounded-2xl bg-gradient-to-br from-emerald-50 to-white border border-emerald-100 hover-lift">

<div className="w-16 h-16 mx-auto bg-gradient-to-br from-emerald-500 to-emerald-600 rounded-2xl flex items-center justify-center mb-6">

<MapPin className="w-8 h-8 text-white" />

</div>

<h3 className="text-xl font-bold mb-3">Hyperlocal Matching</h3>

<p className="text-gray-600">AI connects donors with the nearest recipients in real-time, ensuring food reaches those in need quickly.</p>

</div>

<div className="text-center p-8 rounded-2xl bg-gradient-to-br from-orange-50 to-white border border-orange-100 hover-lift">

<div className="w-16 h-16 mx-auto bg-gradient-to-br from-orange-500 to-orange-600 rounded-2xl flex items-center justify-center mb-6">

<Zap className="w-8 h-8 text-white" />

</div>

<h3 className="text-xl font-bold mb-3">Instant Notifications</h3>

<p className="text-gray-600">Recipients get immediate alerts about available food nearby, with real-time status updates.</p>

</div>

<div className="text-center p-8 rounded-2xl bg-gradient-to-br from-blue-50 to-white border border-blue-100 hover-lift">

<div className="w-16 h-16 mx-auto bg-gradient-to-br from-blue-500 to-blue-600 rounded-2xl flex items-center justify-center mb-6">

<Shield className="w-8 h-8 text-white" />

</div>

<h3 className="text-xl font-bold mb-3">Safe & Verified</h3>

<p className="text-gray-600">Food safety guidelines, verified users, and transparent communication ensure trust and quality.</p>

</div>

</div>

</div>

</section>

{/\* Stats \*/}

<section className="py-20 bg-gradient-to-br from-emerald-600 to-emerald-700 text-white">

<div className="container mx-auto px-4">

<div className="grid md:grid-cols-3 gap-8 max-w-4xl mx-auto text-center">

<div>

<TrendingUp className="w-12 h-12 mx-auto mb-4 opacity-90" />

<div className="text-5xl font-bold mb-2">0</div>

<div className="text-emerald-100">Meals Saved</div>

</div>

<div>

<Users className="w-12 h-12 mx-auto mb-4 opacity-90" />

<div className="text-5xl font-bold mb-2">0</div>

<div className="text-emerald-100">Active Users</div>

</div>

<div>

<Heart className="w-12 h-12 mx-auto mb-4 opacity-90" />

<div className="text-5xl font-bold mb-2">0</div>

<div className="text-emerald-100">Communities Served</div>

</div>

</div>

</div>

</section>

{/\* CTA \*/}

<section className="py-20">

<div className="container mx-auto px-4">

<div className="max-w-3xl mx-auto text-center bg-gradient-to-br from-orange-50 to-emerald-50 rounded-3xl p-12 border border-orange-100">

<h2 className="text-4xl font-bold text-gray-900 mb-4">Ready to Make an Impact?</h2>

<p className="text-lg text-gray-600 mb-8">Join our community of donors and recipients working together to end food waste and hunger.</p>

<Button

onClick={handleGetStarted}

className="bg-gradient-to-r from-emerald-600 to-orange-500 hover:from-emerald-700 hover:to-orange-600 text-white px-8 py-6 text-lg rounded-xl shadow-lg hover:shadow-xl transition-all"

>

Get Started Now <ArrowRight className="ml-2 w-5 h-5" />

</Button>

</div>

</div>

</section>

</div>

);

}

**MATCHING ENGINE OF FOODLOOP**:

// Matching algorithm utilities for FoodLoop

// Calculates match scores between listings and recipients

// Configuration

const CONFIG = {

RADIUS\_KM: 5,

PICKUP\_WINDOW\_HOURS: 2,

WEIGHTS: {

distance: 0.6,

freshness: 0.25,

urgency: 0.15,

},

};

// Haversine distance calculation

export function calculateDistance(lat1, lng1, lat2, lng2) {

const R = 6371; // Earth's radius in km

const dLat = (lat2 - lat1) \* Math.PI / 180;

const dLng = (lng2 - lng1) \* Math.PI / 180;

const a =

Math.sin(dLat / 2) \* Math.sin(dLat / 2) +

Math.cos(lat1 \* Math.PI / 180) \* Math.cos(lat2 \* Math.PI / 180) \*

Math.sin(dLng / 2) \* Math.sin(dLng / 2);

const c = 2 \* Math.atan2(Math.sqrt(a), Math.sqrt(1 - a));

return R \* c;

}

// Calculate freshness score (0-1, higher = fresher)

export function calculateFreshnessScore(expiryTime) {

const now = new Date();

const expiry = new Date(expiryTime);

const hoursUntilExpiry = (expiry - now) / (1000 \* 60 \* 60);

if (hoursUntilExpiry <= 0) return 0;

if (hoursUntilExpiry >= 24) return 1;

return Math.max(0, Math.min(1, 1 - (hoursUntilExpiry / 24)));

}

// Calculate distance score (0-1, higher = closer)

export function calculateDistanceScore(distanceKm) {

return 1 / (distanceKm + 0.1);

}

// Calculate match score

export function calculateMatchScore(listing, recipient) {

const distance = calculateDistance(

listing.location\_lat,

listing.location\_lng,

recipient.location\_lat,

recipient.location\_lng

);

if (distance > CONFIG.RADIUS\_KM) return null; // Outside radius

const distanceScore = calculateDistanceScore(distance);

const freshnessScore = calculateFreshnessScore(listing.expiry\_time);

const urgencyScore = recipient.urgency\_score || 0.5;

const matchScore =

CONFIG.WEIGHTS.distance \* distanceScore +

CONFIG.WEIGHTS.freshness \* freshnessScore +

CONFIG.WEIGHTS.urgency \* urgencyScore;

return {

score: matchScore,

distance\_km: distance,

distanceScore,

freshnessScore,

urgencyScore,

};

}

// Find best matches for a listing

export function findBestMatches(listing, recipients, topN = 3) {

const matches = [];

for (const recipient of recipients) {

if (!recipient.location\_lat || !recipient.location\_lng) continue;

const matchData = calculateMatchScore(listing, recipient);

if (matchData) {

matches.push({

recipient,

...matchData,

});

}

}

// Sort by score descending

matches.sort((a, b) => b.score - a.score);

return matches.slice(0, topN);

}

// Check if listing is expired

export function isListingExpired(expiryTime) {

return new Date(expiryTime) < new Date();

}

// Get freshness indicator (green/yellow/red)

export function getFreshnessIndicator(expiryTime) {

const now = new Date();

const expiry = new Date(expiryTime);

const hoursUntilExpiry = (expiry - now) / (1000 \* 60 \* 60);

if (hoursUntilExpiry <= 0) return { color: 'red', label: 'Expired', value: 0 };

if (hoursUntilExpiry <= 2) return { color: 'red', label: 'Expiring Soon', value: hoursUntilExpiry };

if (hoursUntilExpiry <= 6) return { color: 'yellow', label: 'Moderate', value: hoursUntilExpiry };

return { color: 'green', label: 'Fresh', value: hoursUntilExpiry };

}

// Format distance for display

export function formatDistance(distanceKm) {

if (distanceKm < 1) {

return `${Math.round(distanceKm \* 1000)} m`;

}

return `${distanceKm.toFixed(1)} km`;

}

// Estimate time to pickup (rough estimate)

export function estimatePickupTime(distanceKm) {

// Assuming 30 km/h average urban speed

const hours = distanceKm / 30;

const minutes = Math.round(hours \* 60);

if (minutes < 5) return '< 5 min';

if (minutes < 60) return `${minutes} min`;

return `${Math.round(hours \* 10) / 10} hour`;

}

**BACKEND LISTING(DATABASE) :**

{

"name": "Listing",

"type": "object",

"properties": {

"donor\_id": {

"type": "string",

"description": "User ID of the donor"

},

"donor\_name": {

"type": "string",

"description": "Donor name for display"

},

"title": {

"type": "string",

"description": "Title of the food listing"

},

"meals\_count": {

"type": "number",

"description": "Number of meals/servings available"

},

"prep\_time": {

"type": "string",

"format": "date-time",

"description": "When the food was prepared"

},

"expiry\_time": {

"type": "string",

"format": "date-time",

"description": "When the food expires/must be collected by"

},

"storage": {

"type": "string",

"enum": [

"hot",

"cold",

"room\_temperature"

],

"description": "Storage requirement"

},

"photo\_urls": {

"type": "array",

"items": {

"type": "string"

},

"description": "URLs of uploaded photos"

},

"location\_lat": {

"type": "number",

"description": "Pickup location latitude"

},

"location\_lng": {

"type": "number",

"description": "Pickup location longitude"

},

"address": {

"type": "string",

"description": "Pickup address"

},

"pickup\_instructions": {

"type": "string",

"description": "Instructions for pickup"

},

"status": {

"type": "string",

"enum": [

"available",

"matched",

"collected",

"expired",

"cancelled"

],

"default": "available",

"description": "Current status of listing"

},

"matched\_to": {

"type": "string",

"description": "User ID of matched recipient"

},

"matched\_to\_name": {

"type": "string",

"description": "Name of matched recipient"

},

"priority\_score": {

"type": "number",

"description": "Computed priority score for matching"

}

},

"required": [

"title",

"food\_type",

"meals\_count",

"expiry\_time"

]

}

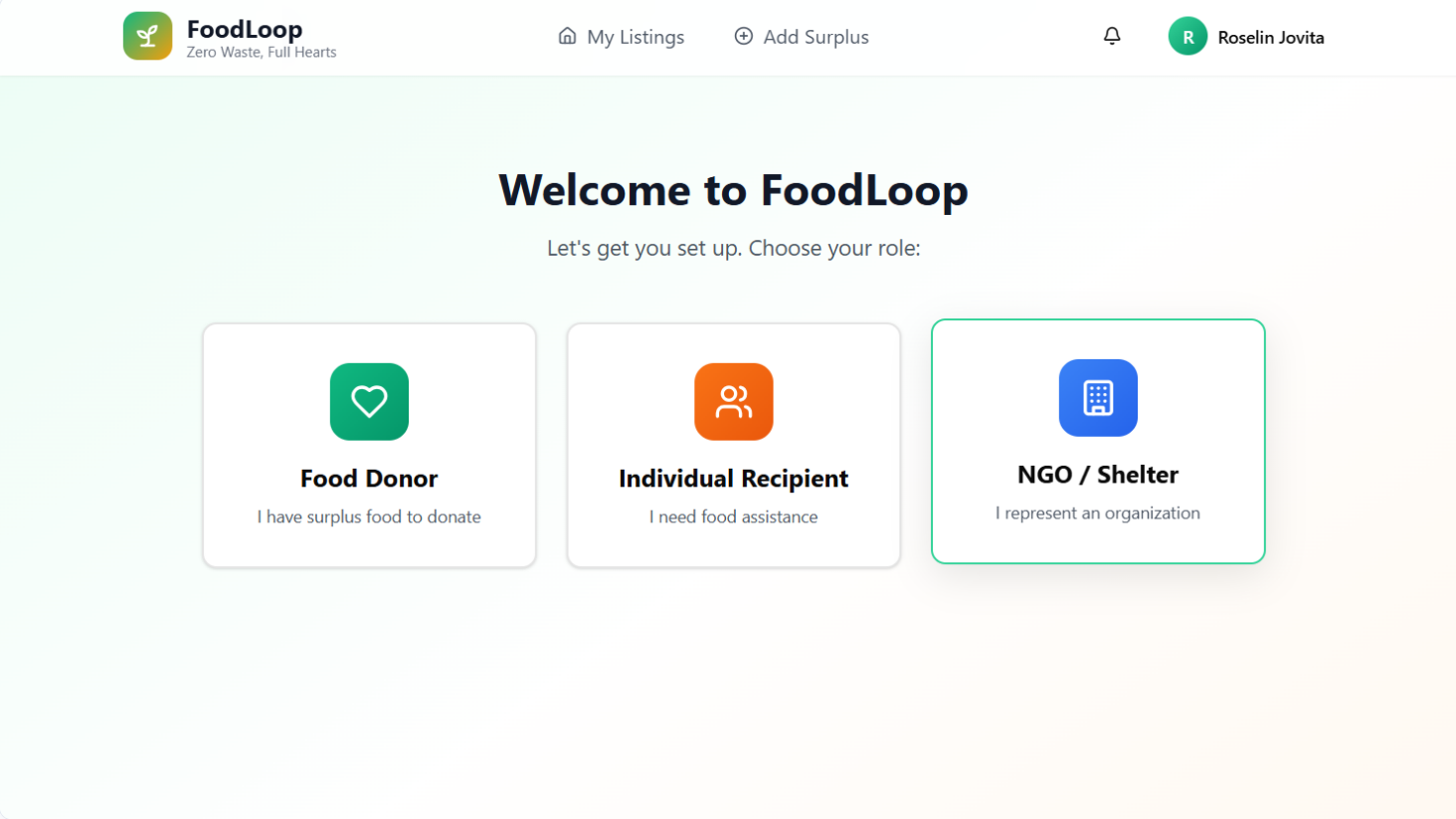
# Chapter 10

# APPENDIX 2 – SAMPLE OUTPUT

## 10.1 Home Page

The project output screenshots are shown as follows:

#### Homepage

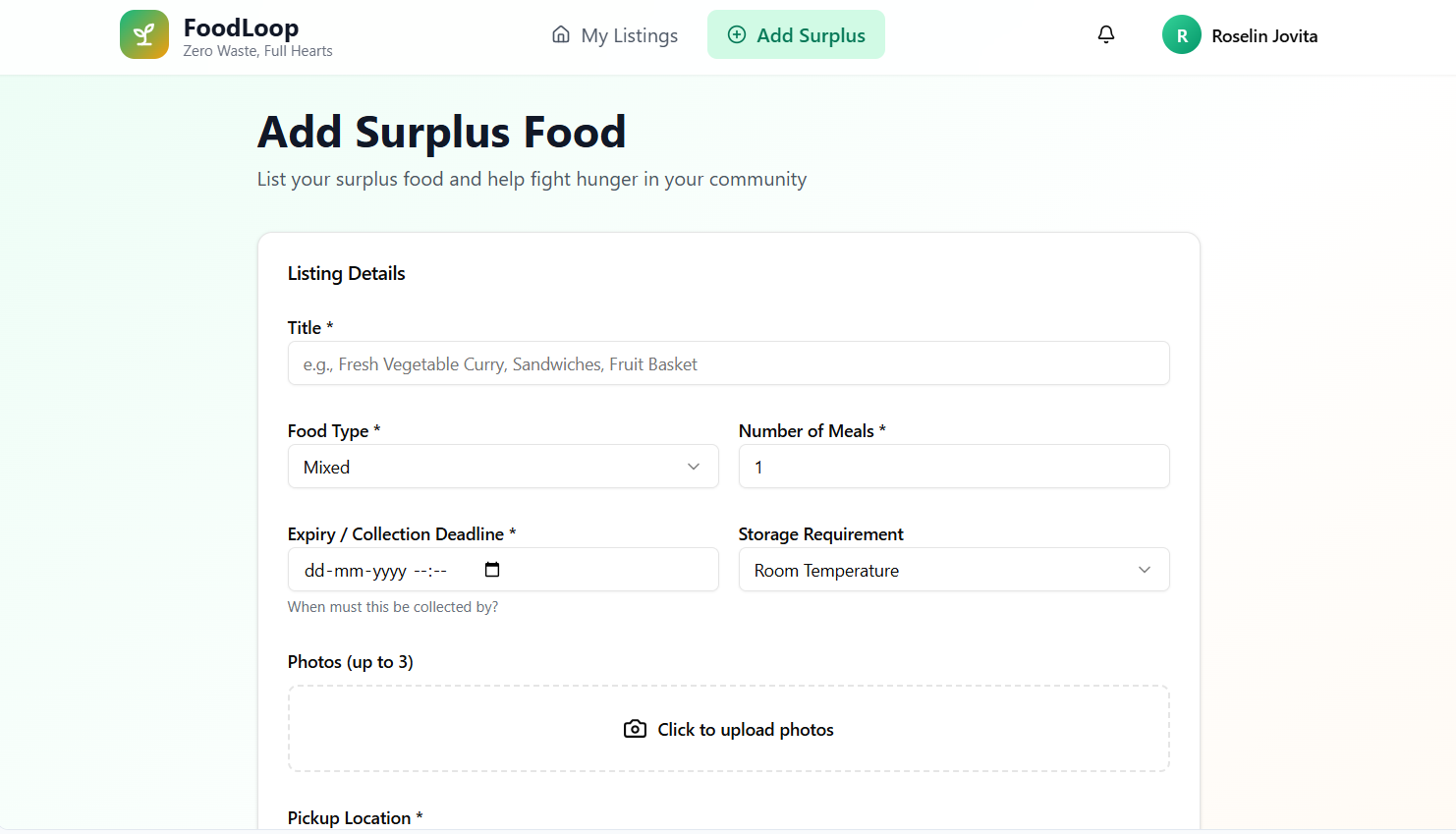


The Home Page serves as the entry point to the FoodLoop Intelligent Food Recommendation System, providing users with a simple and user-friendly interface to begin receiving personalized food suggestions. Users are welcomed with a clean layout that allows easy access to account login or preference selection. The interface enables users to enter dietary requirements, preferred cuisines, health goals, or location details to customize their recommendation experience.

To start the recommendation process, users submit their preferences by clicking the “Get Recommendations” button. Once submitted, the system analyzes the input data using trained deep learning recommendation models to generate accurate and personalized food suggestions. The primary objective of this page is to offer smooth navigation and quick interaction with the system.

## Add Surplus Food

#### Add surplus food



After processing user inputs, the system displays a list of recommended food items or restaurants, categorized into priority levels such as “Highly Recommended,” “Recommended,” and “Suggested.”

**Highly Recommended:**

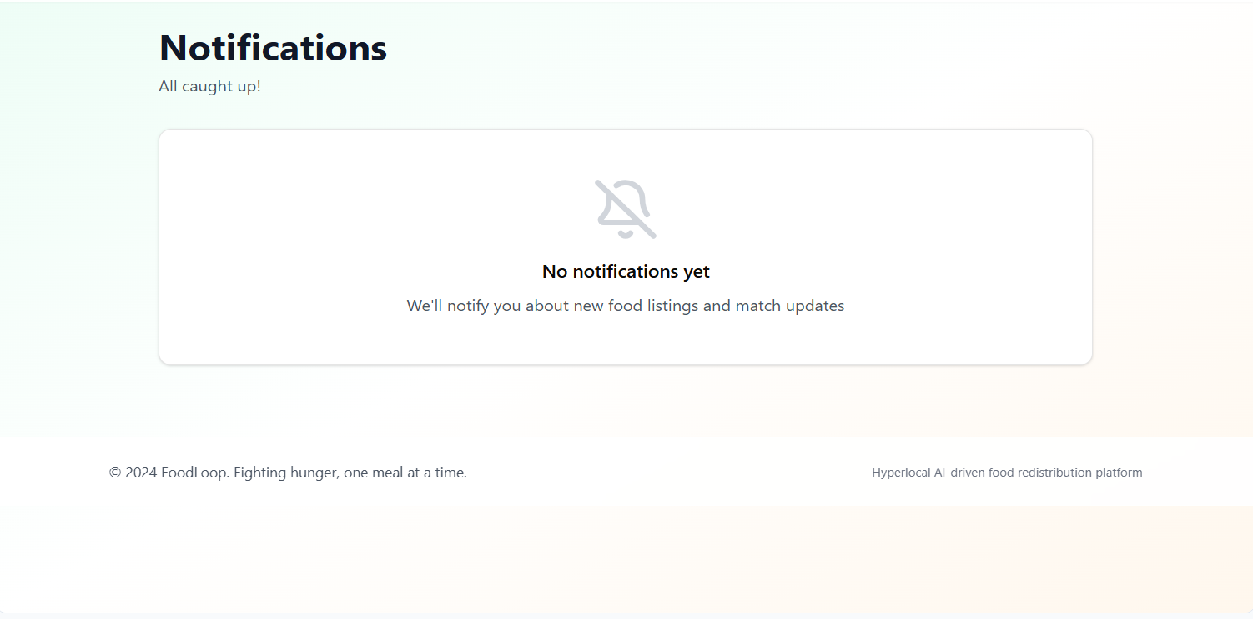
Items with the highest preference match probability are displayed at the top, highlighting the best-suited food choices for the user based on previous interactions and dietary goals.

**Recommended:**

Foods that closely match user preferences are suggested as alternative options

## Notification Message

#### 10.3 Notification Message



The notification feature provides quick alerts to users regarding personalized recommendations, exclusive discounts, diet reminders, or nearby restaurant suggestions. Messages are concise yet informative, containing key details such as food item names, preference match probability, restaurant location, and estimated preparation or delivery time.

These alerts enable users to make faster decisions while enhancing engagement and convenience. By offering real-time updates and smart notifications, FoodLoop ensures an interactive, responsive, and highly personalized user experience aimed at simplifying food discovery and improving overall satisfaction.

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